Same People, Different Places: Geographic Context and Vote Choice in the Trump Electorate*

Jessica Persano‡

March 2026

Abstract

Does geographic context independently shape presidential vote choice, or does the urban-rural political divide simply reflect who lives where? Using the Stanford-Arizona State-Yale 2024 Election Study ($N = 84{,}837$), I test whether community type independently predicts Trump vote choice after controlling for race, education, income, age, and gender. Rural residents are 18.97 percentage points more likely to vote for Trump than demographically identical city residents, a gap that persists across regional controls and ten robustness checks. Among consistent major-party voters, the geographic gap shows little to no variation across the three Trump-era elections. The gap is substantially larger among white voters than non-white voters, and within the white electorate college-educated whites exhibit only a slightly larger rural gap than non-college whites. A mediation analysis finds that gun ownership, issue salience, immigration attitudes, and climate attitudes together account for approximately 76 percent of the rural effect. Separately, adding partisan identification and ideological self-placement to the baseline model reduces the rural effect by 93 percent, suggesting that geography operates primarily through its long-run influence on partisan identity formation. This paper offers the first large-sample, individual-level test of the compositional-versus-contextual question spanning all three Trump-era elections, suggesting America's geographic partisan divide is structural rather than demographic and unlikely to narrow without changes to the community-level environments that sustain it.

Keywords: urban-rural divide, geographic polarization, presidential vote choice, contextual effects, Trump electorate

*Final Term Paper: PS427F The American Electorate in the Trump Era, Stanford University.

†Pre-Doctoral Research Fellow, Graduate School of Business, Stanford University

‡Replication materials are available at https://github.com/JessicaPersano/trump-geographic-divide.

1 Introduction

The 2024 presidential election deepened a geographic cleavage that is increasingly central to American electoral politics, with Donald Trump controlling much of rural America and Kamala Harris carrying the nation's cities. According to the Stanford-Arizona State-Yale 2024 Election Study (SAY24), the gap in Trump support between rural and urban respondents as of October 2024 exceeded twenty-eight percentage points, with rural voters backing Trump at a rate of 66.6 percent compared to 37.7 percent in cities (Stanford University, Arizona State University, and Yale University, 2024). The scale of this divide has led many analysts to frame the working-class realignment of the past decade as, in significant part, a geographic story: a rupture between places, not just between kinds of people. That rupture has consequences beyond electoral preference: under winner-take-all institutions, the geographic concentration of partisan coalitions produces systematic disparities in political power and representation, making the question of why places vote differently a matter of democratic stakes that extend well beyond any single election (Rodden, 2019).

The dominant explanation for this divide is compositional. Rural areas are disproportionately white, less formally educated, older, and lower-income than cities, and each of these characteristics independently predicts Republican presidential vote choice. Under a purely compositional account, the geographic pattern is incidental: it reflects who happens to live where, not anything about the places themselves. But this account is incomplete if geographic context (the social networks, information environments, local economies, and issue priorities that differ systematically across urban and rural communities) exerts an independent influence on political behavior beyond the characteristics of the individuals residing there. This paper asks precisely that question: do voters with identical demographic profiles vote differently depending on whether they live in a city, a suburb, a town, or a rural area?

If the urban-rural divide is purely compositional, then the realignment is a story about individuals—about the political behavior of white non-college workers, older rural voters, and so on—and the geographic pattern follows automatically from the sorting of these groups across space. If the divide has an independent contextual component, then two white non-college workers in different community contexts may respond differently to the same candidates and the same campaign, because the communities they inhabit have shaped their partisan identities, their issue priorities, and their political information environments in systematically different ways. Not only are these fundamentally different accounts of the same electoral phenomenon, but they hold vastly different implications. The first implies that the geographic pattern is a consequence of demographic trends and will follow wherever those demographics lead. The second implies that the places themselves are doing political work: the rural community, as a social and informational environment, pushes voters toward a distinct political identity that transcends individual characteristics.

Distinguishing between these accounts requires individual-level data: if the compositional explanation is correct, controlling for each respondent's own demographic characteristics should eliminate the geographic gap in vote choice entirely. Thus, I test this question using the Stanford-Arizona State-Yale 2024 Election Study, a large-scale panel survey conducted by YouGov with over 100,000 respondents across multiple waves. My primary analysis draws on the October 2024 baseline wave, which provides 84,837 respondents with valid vote choice and complete demographic information—sufficient statistical power to detect meaningful differences within narrow demographic subgroups. Survey-weighted logistic regression models with reported average marginal effects allow for the estimation of the independent effect of community type on the probability of voting for Trump, net of a full set of demographic controls.

The results present a mixed picture. Geographic context exerts a large and robust independent effect on vote choice: after controlling for race, education, income, age, and gender, rural residents are approximately 19 percentage points more likely to vote for Trump than demographically identical city residents, a gap that survives regional controls and ten alternative specifications. Contrary to prevailing narratives of accelerating geographic polarization, this gap has remained structurally stable across all three Trump-era elections. Furthermore, while it is substantially larger among white voters than non-white voters, the education gradient within the white electorate runs in a surprising direction. Gun ownership, immigration attitudes, climate attitudes, and issue priorities together account for the majority of this geographic effect, with partisan identity accounting for nearly all of it. These results suggest that place shapes the vote primarily through its long-run influence on partisan identity formation.

With these findings, this paper makes three specific contributions to the literature on geographic polarization and the Trump-era realignment. First, it provides the first large-sample, individual-level test of the compositional-versus-contextual question spanning all three elections in which Trump has appeared on the presidential ballot (2016, 2020, 2024), and extends the foundational work of Gimpel et al. (2020) from party identification to vote choice. Second, it establishes that the geographic gap has remained structurally stable across this period, a finding that complicates prevailing narratives of accelerating geographic polarization. Third, it provides a formal empirical test of whether issue-based differences, specifically geographic variation in most-important-issue prioritization, gun ownership rates, immigration attitudes, and climate attitudes, partially mediate the geographic effect on vote choice, a mechanism the theoretical literature has posited but has not examined at this scale with individual-level data.

The remainder of this paper proceeds as follows. Section 2 reviews the empirical literature on geographic polarization in American elections. Section 3 develops the theoretical mechanisms through which place may independently shape political behavior and derives the three hypotheses from that framework. Section 4 describes the data, variables, and analytical strategy. Section 5 presents the results of the core analysis, the over-time comparison, the race-and-education subgroup analysis, and the mediation analysis. Section 6 interprets the findings and discusses their implications for the study of the Trump-era realignment. Section 7 concludes.

2 Literature Review

The urban-rural divide in American presidential voting is well-documented and has deepened considerably over recent decades. Scala and Johnson (2017) find that polarization along the rural-urban continuum steepened considerably from 2000 to 2016, and Pautonnier et al. (2026) documents that the divide now exceeds both the gender gap and the income gap in magnitude. Brown and Mettler (2024) trace its development from 1976 to 2020, finding that the sharpest acceleration occurred in the decade before Trump's first candidacy and suggesting the partisan geography of the Trump era consolidated a realignment already well underway rather than initiating one. That divide, however, is not uniform across the electorate: Teigen et al. (2017) find that geographic context has virtually no effect on Black voters' presidential vote choice, a pattern Brown et al. (2025) confirm holds more broadly, with Black and Latino voters exhibiting minimal geographic differences in vote choice compared to white Americans. The central debate in the literature concerns not whether this divide exists, but what produces it, a question that turns on the distinction between compositional and contextual explanations.

This section reviews the compositional account and its empirical limitations, the individual-level evidence for independent contextual effects, and presents the specific gap in the literature this paper addresses.

2.1 The Compositional Explanation

The most influential account of geographic polarization in American electoral politics holds that the urban-rural divide is a compositional phenomenon: it reflects the concentration of certain kinds of voters in certain kinds of places, rather than any causal effect of place itself on political behavior. Under this account, rural areas vote Republican in presidential elections because they contain disproportionate shares of white, non-college-educated, older, and religiously observant voters, which represent groups that have moved toward the Republican Party through a series of party system changes spanning several decades. If these demographic characteristics were distributed randomly across geographic contexts, the argument implies, the rural-urban divide in vote choice would disappear. The empirical case for this account rests primarily on aggregate, county-level data—a foundation that, as discussed below, carries an important inferential limitation.

Albrecht (2022), using county-level data from 2016 and 2020, find that the rural-urban coefficient in models of Trump vote share largely disappears when the proportions of non-Hispanic white residents and non-college-educated residents are included as controls, suggesting that the geographic pattern is a statistical artifact of demographic concentration. Wilkinson (2019) offers a theoretical account of why: urbanization has filtered populations on ethnicity, educational attainment, and personality traits associated with openness to experience, producing the partisan geography observed today. On this account, the sorting of voters across communities is the primary phenomenon, and the geography of elections follows as a consequence.

However, the inferential problem is straightforward. When a county-level model controls for the proportion of non-Hispanic white residents, it adjusts for the aggregate racial composition of the county, not for the race of the individual voter. A county with 85 percent white residents and strong Trump support will register as "explained" by racial composition in aggregate analysis regardless of whether the mechanism is that white voters in that county vote Republican (a compositional effect) or that white and non-white voters alike in high-white-share counties are pushed toward Republican vote choice by their geographic environment (a contextual effect). Therefore, individual-level data that control for each respondent's own demographics are necessary to distinguish between these alternatives.

2.2 Evidence for Independent Contextual Effects

Individual-level studies that control for each respondent's own demographic characteristics consistently find a residual geographic effect that the compositional account cannot fully explain. The most directly comparable prior work is Gimpel et al. (2020), who pool over 100,000 respondents from Gallup monthly surveys conducted between 2003 and 2018 and geocode respondents' locations to produce objective measures of population density and distance from a metropolitan center. After controlling for income, age, race, ethnicity, and religious observance, they find that a voter in the most rural location is approximately 12 percentage points less likely to identify as a strong Democrat than a demographically identical urban voter, and that the full range of population density is associated with a 15-point difference in the probability of Democratic identification, ultimately arguing the rural-urban differentiation "cannot be reduced to an inventory of the commonly observed differences between the populations." Teigen et al. (2017) extend this finding directly to presidential vote choice (the dependent variable of interest here) matching CCES respondents from 2008 and 2012 to ZIP-code-level population density and finding a significant geographic effect after controlling for individual socioeconomic attributes, with higher density predicting Democratic voting concentrated almost entirely among white voters. Both studies leave open the question of whether these effects extend across the Trump era and at the scale necessary for precise subgroup comparisons, gaps this paper is designed to address.

A distinct line of evidence rules out the most straightforward alternative interpretation. If voters simply sort into communities that match their pre-existing political preferences, geography would be a consequence of preferences rather than a cause. Martin and Webster (2020) test this directly using individual-level voter registration records to track the partisan composition of residential moves, finding that the partisan bias in moving decisions is far too small to sustain the observed level of geographic polarization. This rules out the most direct threat to the individual-level design employed here: that the geographic gap in vote choice simply reflects the self-selection of like-minded voters into like-minded communities. What remains to be established is whether the contextual effect documented in these studies holds across all three Trump-era elections, varies systematically by race and education, and operates through identifiable issue-based mechanisms.

2.3 Gap in the Existing Literature

Despite this accumulation of evidence, no peer-reviewed study has examined the compositional-versus-contextual question at the individual level across all three Trump-era presidential elections simultaneously, with a sample large enough to sustain precise subgroup comparisons and a formal test of the issue-based mechanisms through which the geographic effect may operate. Shepherd (2025) uses the 2016–2020–2024 ANES panel to compare place-based, diploma-based, and racial accounts of partisan change, finding that race and place are more central than education. However, the study's relatively small sample size (N = 2,839), its focus on partisanship rather than vote choice, and its unpublished status leave the cross-election test open. This paper works to fill that gap by offering the first large-sample, individual-level test of geographic contextual effects on presidential vote choice spanning all three Trump-era elections, with a formal mediation analysis examining the issue-based channels through which place may shape the vote.

3 Theory and Hypothesis

Establishing that a geographic effect exists is distinct from explaining why it exists. Place shapes political behavior through social networks, information environments, and issue priorities that differ systematically across communities; mechanisms that are slow-moving by nature and operate primarily through long-run identity formation rather than direct effects at the ballot box. From these theoretical foundations, this section derives three testable predictions about the scope, trajectory, and heterogeneity of the geographic effect on vote choice.

Geographic context shapes political behavior through mechanisms that operate above the level of the individual: the social networks through which political information flows, the information environments that structure how voters perceive candidates and parties, and the issue priorities that local economic and social conditions make salient. Critically, these mechanisms are not short-term or election-specific. Social networks are formed through years of local interaction; information environments reflect the long-run structural decline of local news in rural communities; and issue salience is shaped by the enduring economic and social character of places. The theoretical implication is that geographic context should shape political behavior primarily through its influence on the partisan and ideological identities voters form over time, rather than through direct effects at the ballot box, and that this influence should be durable rather than transient.

The first and most fundamental prediction is that geographic context should exert an independent effect on vote choice that survives individual demographic controls. If political behavior were shaped only by individual characteristics, controlling for race, education, income, age, and gender should eliminate the urban-rural gap entirely. But the mechanisms described above are properties of communities, not individuals. The partisan composition of one's social network, the information environment of one's community, and the issue priorities shaped by local economic conditions are not captured by individual demographics, as two voters with identical characteristics but different community contexts encounter systematically different political worlds. Huckfeldt and Sprague (1995) demonstrate that political preferences are transmitted through local networks of trusted discussants, meaning the partisan character of the community shapes individual preferences through repeated social interaction over time. Cramer (2016) shows that rural residents develop a place-based political identity, what they call a "rural consciousness" combining distributional grievance and cultural resentment, that structures vote choice in ways irreducible to individual economic or educational characteristics. These community-level influences generate the expectation that a meaningful geographic gap should persist after demographic controls, and that it should be largest at the extremes of the urban-rural continuum where community context is most politically homogeneous.

The second prediction concerns the trajectory of the geographic gap across the three Trump-era elections. The prevailing narrative in political commentary holds that the urban-rural divide has accelerated under Trump; each successive election has deepened the rupture between rural and urban America. This expectation is not unreasonable: Trump's campaigns have consistently foregrounded issues and cultural appeals that resonate differentially across the rural-urban continuum, potentially activating place-based identities with increasing intensity across cycles. At the same time, the structural mechanisms through which place shapes political behavior are slow-moving by nature: social networks, information environments, and place-based identities consolidate over years rather than election cycles. Whether the geographic gap has genuinely widened, remained stable, or narrowed as Trump's coalition diversified is therefore an open empirical question, and one this paper is positioned to answer with greater precision than prior work given its sample size and cross-election design.

The third prediction concerns heterogeneity in the geographic effect across racial and educational groups. The mechanisms through which place shapes political behavior should not operate uniformly across all voters. For racial and ethnic minorities, racial group identity provides a powerful cross-cutting political anchor, what Dawson (1994) terms "linked fate." This concept describes the sense that individual political outcomes are bound to the outcomes of one's group, which competes directly with place-based community identity as a source of political orientation. Where linked fate is strong, the partisan homogeneity of the local community should exert less pull, because racial group membership provides an alternative and often more politically salient identity. The expectation is therefore that the geographic gap in vote choice should be substantially smaller among non-white voters than among white voters, for whom no comparable cross-cutting group identity competes with geographic community as a primary source of partisan identity. Within the white electorate, the direction of the education gradient is less theoretically clear. The Cramer-Hochschild account of rural consciousness emphasizes working-class place-based identity and distributional grievance, suggesting the geographic gap should be largest among non-college white voters for whom place-based economic resentment is most acute (Cramer, 2016). However, a competing prediction may follow from the logic of selective retention: college-educated voters who remain in rural communities despite credentials enabling relocation may be precisely those for whom place-based identity is most central. These predictions cannot be resolved theoretically, but the former is the more established account and serves as the primary expectation.

Geographic context may also shape vote choice through the issue priorities and policy attitudes it makes salient, rather than solely through social network reinforcement or long-run identity formation. Rural communities have substantially higher rates of gun ownership, distinct patterns of issue prioritization shaped by local economic structure, and systematically different exposures to the policy debates that divided the candidates in 2024. These differences do not require rural and urban voters to hold fundamentally different underlying values, only that different issues become personally salient depending on the economic and social environment of one's community (Borwein et al., 2025). If issue-based differences partially account for the geographic gap in vote choice, they represent a quantifiable channel through which place shapes the ballot—one that prior work has theorized but not directly examined at the individual level with a sample large enough to sustain precise estimates.

Together, these theoretical considerations suggest that the urban-rural gap in presidential vote choice reflects something more than the demographic composition of places: it reflects the political worlds those places create. The three hypotheses that follow test the scope, trajectory, and heterogeneity of this effect; the mediation analysis tests one specific channel through which it operates.

3.1 Hypotheses

This analysis tests three specific hypotheses derived from the theoretical framework above.

> **H1:** Among voters with identical demographic profiles (matched on race, educational attainment, household income, age, and gender), those who live in rural areas are more likely to vote for Donald Trump than those who live in cities, suburbs, or small towns, and this result will persist under additional specifications.

H2: The magnitude of the urban-rural gap in Trump vote choice, after controlling for individual demographics, has remained stable from 2016 to 2024.

H3: The urban-rural gap in Trump vote choice varies systematically with the strength of competing cross-cutting identities: it is larger among white voters than non-white voters, where racial linked fate attenuates place-based community influence, and larger among non-college-educated white voters than college-educated white voters, for whom working-class place-based identity operates with the greatest force.

4 Data and Methodology

This section details the research design used to test whether geographic context independently shapes presidential vote choice after controlling for individual demographic characteristics. It describes the data source and sample construction, operationalizes the primary geographic and demographic variables, outlines the three model specifications used to estimate the independent effect of community type on the probability of voting for Trump, and explains the over-time, subgroup, and mediation analyses used to test the trajectory, heterogeneity, and issue-based mechanisms of the geographic effect.

4.1 Data and Sample

This paper utilizes the Stanford-Arizona State-Yale 2024 Election Study (SAY24), a large-scale panel survey conducted by YouGov in collaboration with researchers at Stanford University, Arizona State University, and Yale University. SAY24 surveyed over 100,000 respondents from YouGov's U.S. panel between December 2023 and January 2025, recontacting each respondent multiple times across the full arc of the 2024 presidential campaign. YouGov administered the survey using its proprietary online panel, selecting respondents via sample matching to produce a nationally representative sample. All analyses use the survey weights provided by YouGov, which are calibrated to national population benchmarks via sample matching. SAY24 is particularly well-suited to testing geographic contextual effects for three reasons. First, its sample size (over 100,000 respondents in a single baseline wave) provides sufficient statistical power to compare demographically similar voters across geographic categories within narrow subgroups. Second, SAY24 includes a self-reported urban-rural measure classifying respondents as living in a city, suburb, town, rural area, or other, which maps directly onto the continuum central to this paper's hypotheses. Third, the survey contains retrospective vote questions for 2016 and 2020 alongside the 2024 vote outcome, enabling a cross-election trend comparison within a single large-sample dataset. The primary data source is the October 2024 baseline wave (N = 109,255). This wave was chosen because it was fielded in the final weeks before the election (the point where vote intentions are most settled), was the largest single wave in the panel, and contained the recalled vote measures required for H2.

The primary analysis sample consists of 84,837 respondents from the October 2024 baseline wave of the survey. Beginning with the total number of 109,255 observations, I exclude 933 respondents reporting "other" as their community type, 13,003 respondents with missing values on any demographic control variable, and 10,482 respondents who reported not voting, chose a third-party candidate, or were unsure of their 2024 vote choice. The attrition from missing demographics is the largest single exclusion, reflecting the absence of values on income and education for a subset of respondents. Full details on each exclusion step are reported in Table A1 in Appendix A.

4.2 Variables

The primary independent variable is self-reported community type, drawn from the survey question asking respondents to classify their area of residence as a city, suburb, town, rural area, or other. City serves as the reference category throughout, so all geographic effects are estimated as differences relative to city residents. This self-reported measure is preferred because the theoretical mechanisms through which place shapes political behavior, such as social network reinforcement, place-based identity, and issue salience, operate through how voters perceive and identify with their geographic context, not through objective administrative boundaries. A rural voter who identifies strongly with their community is more likely to be embedded in the social and informational environment that place-based theory describes than one who merely happens to live in a low-density zip code by Census classification. Two robustness checks address concerns about the geographic coding. The first collapses the four-category measure to a binary Urban (City and Suburb) versus Rural/Town (Town and Rural) indicator, testing whether the main results depend on treating suburbs as meaningfully distinct from cities (RC4). The second substitutes Census Bureau population density at the zip code tabulation area (ZCTA) level as a continuous objective alternative to the self-reported categorical measure (RC5).

The primary dependent variable is a binary indicator coded 1 for a Trump vote and 0 for a Harris vote, drawn from the pre-election vote intention question in the October 2024 baseline. The variable is restricted to major-party voters because the paper's central question concerns geographic sorting within the competitive two-party choice: including third-party voters in the reference category would conflate qualitatively distinct political behaviors—a protest vote and a sincere Democratic vote are not equivalent expressions of opposition to Trump—and third-party candidates received approximately one to two percent of the national vote in 2024, so their exclusion has minimal consequences for sample composition. Pre-election intention is used in place of post-election recalled vote to avoid social desirability effects and post-hoc rationalization; robustness checks confirm consistent results using post-election reported vote (RC3) and alternative treatments of non-voters (RC1, RC2). For the over-time analysis, respondents' recalled votes in 2020 and 2016 are drawn from the same baseline wave and recoded to the same binary Trump-versus-Democrat frame. Full variable coding details are provided in Appendix B.

4.3 Model Specifications and Analytical Strategy

The analysis proceeds in four stages. The first tests H1 by estimating the independent geographic effect on 2024 vote choice across three model specifications of increasing restrictiveness. The second tests H2 by re-estimating the primary specification separately for 2016, 2020, and 2024 to assess whether the rural-city gap has remained stable across the Trump era. The third tests H3 by estimating geographic effects separately for white non-college, white college, and non-white respondents. The fourth introduces four candidate mediators to assess the mechanisms through which place shapes the vote. Ten robustness checks assess the sensitivity of the primary H1 result to alternative analytical choices, organized in four groups: alternative dependent variable specifications (RC1–3), alternative geographic coding (RC4–5), alternative model specifications (RC6–7), and subgroup and stability checks (RC8–10). Formal specifications for all models and robustness checks are provided in Appendix C; full robustness check results are reported in Appendix D.

4.3.1 Analytical Strategy

All models are estimated via survey-weighted logistic regression using the `svyglm()` function in R, incorporating YouGov survey weights throughout. Logistic regression is appropriate because the dependent variable is binary; unlike OLS, it models the log-odds of the outcome as a linear function of predictors and constrains predicted probabilities to the unit interval. The `quasibinomial()` family is used in place of the standard `binomial()` family because survey weights inflate the effective sample size, which would cause a standard binomial model to underestimate standard errors. The quasibinomial estimator introduces a dispersion parameter that corrects for this inflation, producing the same point estimates as binomial logistic regression but with appropriately conservative standard errors that better reflect sampling uncertainty under the complex survey design.

The primary quantity of interest in all stages is the average marginal effect (AME) of community type on the probability of voting for Trump (the average change in predicted vote probability associated with living in each geographic category relative to city residents) evaluated at each respondent's observed covariate values and averaged across the full sample. AMEs are preferred over log-odds coefficients because they are on the probability scale and directly interpretable as percentage-point differences in the likelihood of a Trump vote. They are also preferred over marginal effects evaluated at the mean, which in nonlinear models can be unrepresentative of the actual population distribution; averaging over observed covariate values instead produces an estimate that better reflects the sample as a whole. AMEs are computed using the `marginaleffects` package's `avg_slopes()` function

4.3.2 H1: Geographic Effect on 2024 Vote Choice

Three model specifications are estimated and reported jointly. Model 1 includes five demographic controls: race (White, Black, Hispanic, and Other), educational attainment (high school or less, some college, college graduate, and postgraduate), age (under 30, 30–44, 45–64, and 65 and older), gender (binary indicator for female), and household income (under \$50,000, \$50,000–\$100,000, and over \$100,000). This model constitutes the primary test of whether geographic context predicts vote choice net of individual composition. These five variables are the characteristics that the purely compositional explanation for geographic polarization holds responsible for the urban-rural gap. Model 2 adds census region (Northeast, Midwest, South, and West) to assess whether the geographic gap is an artifact of the regional concentration of rural areas in the South and Midwest rather than a within-region phenomenon. Model 3 adds a seven-point party identification scale and a five-point ideological self-placement scale to the previous controls. Because partisan identity and ideology may themselves be downstream products of geographic context (shaped by the social networks and information environments that place provides) these variables are treated as potential mediators rather than pure confounders, and the attenuation from Model 1 to Model 3 is therefore informative about the pathway through which place shapes the vote.

4.3.3 H2: Over-Time Trend

The over-time comparison re-estimates the Model 1 specification separately for 2016, 2020, and 2024 vote choice. Geographic AMEs are compared across the three elections to assess whether the rural-city contrast has grown, narrowed, or remained stable. Because recalled vote is subject to well-documented biases (for example, respondents who currently support Trump may be more likely to recall having voted for him in prior cycles, which would bias the over-time comparison in the direction of a declining gap) these comparisons should be treated as approximate rather than definitive. Because respondents also differ in whether they can recall a valid major-party vote for all three elections, I additionally present a balanced-panel analysis restricting the comparison to respondents with non-missing vote recall in all three years. This restriction produces a substantively different picture of the over-time trend and is therefore reported as a core finding alongside the main estimates rather than as a sensitivity check.

4.3.4 H3: Heterogeneity by Race and Education

The subgroup analysis estimates the Model 1 specification separately for three mutually exclusive groups: white non-college respondents, white college respondents, and non-white respondents. I then compare geographic AMEs across these groups. White subgroup models omit race and education controls (which are constant within each stratum by construction); the non-white model retains both. This stratified approach allows the racial and educational dimensions of geographic heterogeneity to be assessed simultaneously without imposing the constraint that the geographic effect interacts with education in the same way across racial groups.

4.3.5 Mechanism Analysis

The mechanism analysis introduces four candidate mediating variables, each selected because it exhibits systematic rural-urban variation in the SAY24 data and corresponds to a substantive domain central to the 2024 campaign. Gun ownership reflects the substantially higher rates of personal firearm ownership in rural communities and the salience of gun policy to rural political identity (Joslyn, 2025). Issue salience captures whether rural and urban voters prioritize systematically different problems, independent of any single policy domain. Immigration and climate attitudes represent the two policy areas most sharply dividing the 2024 candidates and most consistently varying across the rural-urban continuum in prior survey research.

Gun ownership is a binary indicator coded 1 if the respondent personally owns a gun and 0 otherwise,[1]. Issue salience is captured by a most-important-problem (MIP) variable asking respondents to identify the single most important problem facing the country from a list of sixteen options including jobs and the economy, immigration, inflation, climate change, abortion, guns, and crime. Immigration attitudes are captured by a binary indicator coded 1 if the respondent prefers to see immigration levels decreased and 0 otherwise. Climate attitudes are captured by a binary indicator coded 1 if the respondent prefers to prioritize other issues over climate change and 0 if the respondent prefers to do more to address climate change.

Because each mediator is available for a different subset of respondents due to item non-response, the analytic sample varies across models. Therefore, to ensure that any attenuation in the rural AME reflects the addition of the mediating variable rather than a change in sample composition, I first re-estimate the geographic-only Model 1 specification on each mediator's subsample to establish a within-sample baseline. I then add each mediator individually, starting with issue salience (Model 4a), then gun ownership (Model 4b), immigration attitudes (Model 4c), and climate attitudes (Model 4d), and finally add all four simultaneously (Model 4e). The attenuation in the rural AME between baseline and augmented models, expressed both in percentage points and as a share of the baseline effect, is the primary quantity of interest. This approach follows the logic of observational media-

[1] Respondents in gun-owning households who do not personally own are coded 0, distinguishing personal ownership from household exposure to firearms

tion and is reported as suggestive rather than causal, since observational mediation cannot rule out unmeasured confounders. Subsample sizes range from 76,576 (Model 4e) to 84,698 (Model 4a); full details are reported in Table A2 in Appendix A.

4.4 Methodological Limitations

Four limitations of this research design merit discussion. First, the self-reported community type measure may not align perfectly with objective geographic classifications, and the four categories may compress meaningful within-category variation: a suburb of Dallas and a suburb of Burlington, Vermont are both coded as "suburb" despite differing substantially in density and political environment. The ZCTA population density robustness check (RC5) and binary urban/rural robustness check (RC4) address this directly. Second, the recalled vote measures for 2016 and 2020 are subject to well-documented biases, which would likely inflate the 2016 and 2020 geographic AMEs relative to the true values and bias the over-time comparison in the direction of a declining gap. Accordingly, the over-time comparisons should be treated as approximate rather than definitive. Third, the observational mediation analysis for gun ownership, issue salience, immigration attitudes, and climate attitudes cannot establish causation: all four variables are correlated with community type and with vote choice through multiple pathways, and unmeasured confounders may account for part of the apparent attenuation. Fourth, SAY24's online panel format may under-represent the most geographically isolated rural respondents, particularly those without reliable internet access, even after survey weighting. If the most isolated rural residents are both less likely to appear in the sample and more likely to vote for Trump, the rural AME reported here would be attenuated, suggesting the true contextual effect is at least as large as the estimates reported here, if not larger.

5 Results

This section presents the empirical results in six stages: descriptive patterns in Trump support across geographic categories; a test of H1 (persistence after demographic controls); a test of H2 (stability over time); a test of H3 (variation by race and education); a mediation analysis examining how much issue priorities, gun ownership, and policy attitudes account for the geographic effect; and a summary of ten robustness checks.

5.1 Descriptive Findings

Rural and urban communities in the SAY24 sample differ substantially in their demographic composition, reflecting the broader patterns of geographic sorting that motivate this paper's central question. As shown in Table 1, rural areas are markedly whiter (79.5 percent) than cities (52.8 percent), with higher shares of non-college-educated residents (77.2 versus 61.3 percent) and lower shares of young adults: only 8.0 percent of rural respondents are under 30, compared to 26.8 percent in cities. These compositional differences are precisely what the compositional account predicts: the demographic groups most likely to support Trump are concentrated in the geographic areas where Trump runs strongest.

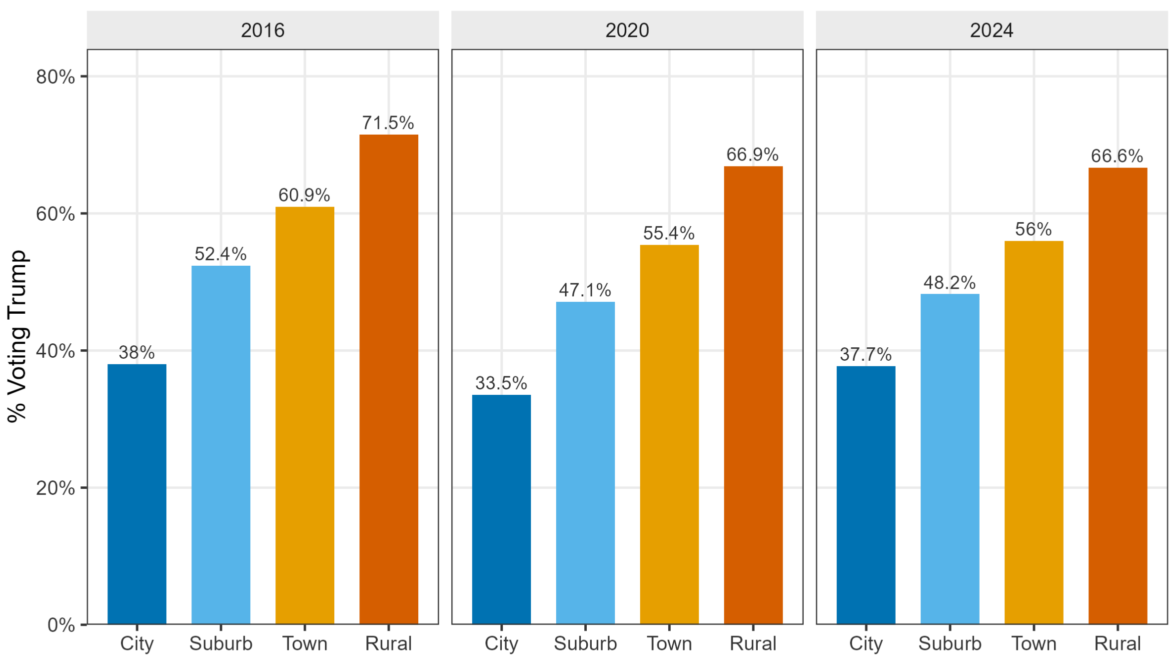
Table 1: **Demographic Composition by Geographic Community Type, 2024**

	City	Suburb	Town	Rural
N (unweighted)	26,248	38,065	12,934	18,072
% White	52.8	67.7	72.5	79.5
% Non-college	61.3	58.7	70.4	77.2
% Female	47.8	51.1	53.8	56.8
% Under 30	26.8	14.6	17.2	8.0
% 65 or older	14.0	25.0	26.0	28.5
% Low income (<$50K)	47.7	35.5	50.9	53.3

Note. Sample consists of respondents with valid community type and complete demographic information (N = 95,319). Unweighted N reported; all percentages are survey-weighted. Low income defined as household income below $50,000.

The raw differences in Trump support across geographic categories are correspondingly large. As displayed in Figure 1, Trump received 66.6 percent of the two-party vote among rural respondents in 2024, compared to 37.7 percent among city respondents: a raw rural-city gap of 28.9 percentage points. The pattern is consistent across all three election cycles: in 2020, the raw rural-city gap was 33.4 percentage points and in 2016 it was 33.5 percentage points. The modest narrowing of the raw gap from 2016 to 2024 likely reflects a combination of factors: Trump's rural two-party share fell between 2016 and 2020 but was essentially flat thereafter, while his city share fell between 2016 and 2020 before recovering substantially between 2020 and 2024, a pattern consistent with the well-documented urban working-class shift toward Trump and with differential changes in third-party voting across geographic categories. Whether this narrowing persists after controlling for demographic composition is the question addressed in Section 5.3.

Figure 1: **Trump Vote Share by Geographic Community Type, 2016–2024**



Note: Bars display survey-weighted Trump two-party vote share (non-voters and third-party voters excluded) within each geographic category. 2024 measure uses pre-election vote intention (N = 84,837); 2020 and 2016 measures use recalled vote (N = 81,378 and N = 71,622, respectively).

5.2 Does the Geographic Gap Persist After Demographic Controls? (H1)

Table 2 presents average marginal effects from the three logistic regression specifications. The results strongly support H1. In Model 1, which controls for race, education, age, gender, and income, rural residents are 18.97 percentage points more likely to vote for Trump than demographically identical city residents (95% CI: 17.55–20.38, $p < .001$). Small-town residents are 11.18 percentage points more likely to vote Trump (95% CI: 9.58–12.78), and suburban residents are 5.99 percentage points more likely (95% CI: 4.76–7.21). All three contrasts are statistically significant and substantively large. Therefore, the geography-vote relationship is not a statistical artifact of differential demographic composition: a rural voter and a city voter who share the same race, education, income, age, and gender still differ by nearly 19 percentage points in their probability of voting for Trump.

Table 2: **Geographic AME on Trump Vote, 2024**

	Average Marginal Effect (pp)		
Contrast (vs. City)	Model 1 Demographics	Model 2 + Region	Model 3 + PID/Ideology
Suburb	5.99***	5.33***	−0.42
	[4.76, 7.21]	[4.10, 6.55]	[−1.09, 0.26]
Town	11.18***	10.82***	1.05*
	[9.58, 12.78]	[9.22, 12.43]	[0.17, 1.92]
Rural	18.97***	17.77***	1.34**
	[17.55, 20.38]	[16.35, 19.20]	[0.52, 2.17]

Note. Entries are average marginal effects in percentage points with 95% confidence intervals in brackets. City is the reference category. Model 1 controls for race, education, age, gender, and income. Model 2 adds census region. Model 3 adds party identification (7-point scale) and ideological self-placement (5-point scale). Survey weights applied throughout; N = 84,837. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

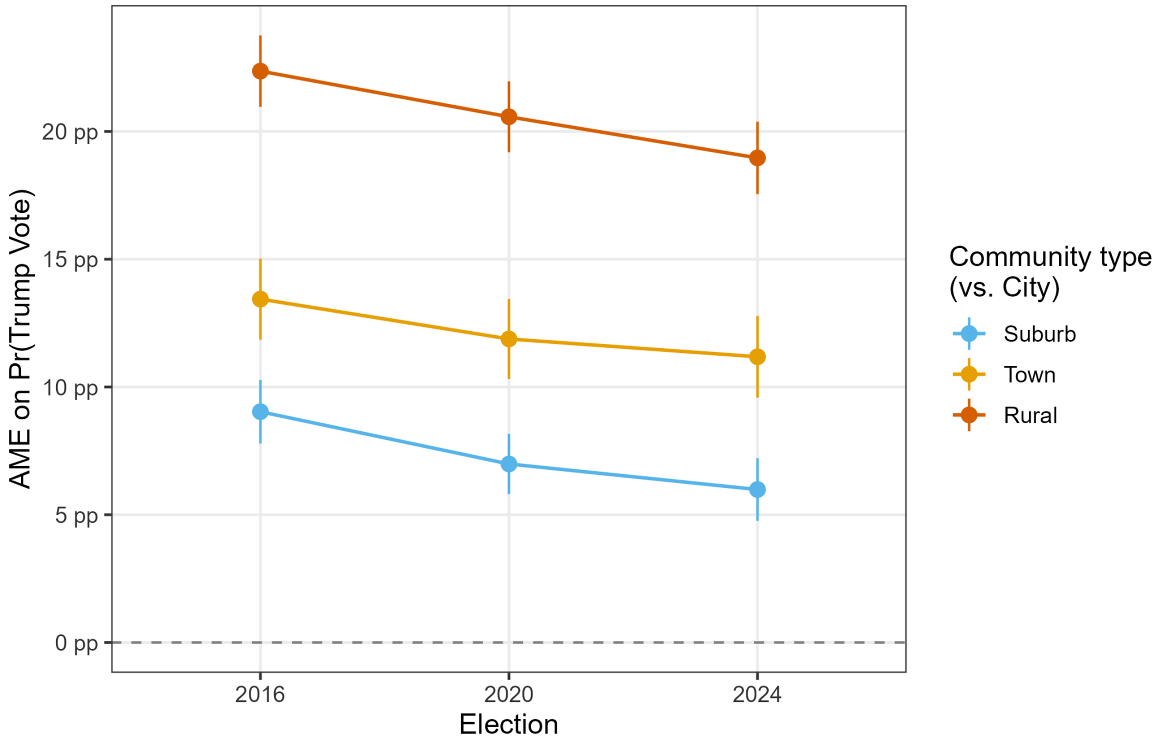
Model 2, which adds census region to the demographic controls, attenuates the rural AME modestly to 17.77 percentage points (95% CI: 16.35–19.20). The slight reduction indicates that some portion of the geographic gap reflects the regional concentration of rural areas in the South and Midwest, where political culture independently predicts higher Republican support. However, the attenuation is small and the geographic effect remains large and precisely estimated. Model 3, which adds party identification and ideological self-placement to the full demographic and regional controls, reduces the rural AME dramatically to 1.34 percentage points (95% CI: 0.52–2.17). This near-complete decline, representing a 93 percent reduction from the Model 1 estimate, indicates that the geographic gap in vote choice is not direct. Instead, geography appears to shape vote choice primarily through the partisan and ideological identities that place-based living helps form. Full log-odds coefficients for all three models are reported in Appendix E. The further interpretation of this finding is taken up in Section 6.

5.3 Has the Geographic Gap Remained Stable Over Time? (H2)

Figure 2 displays geographic AMEs estimated separately for recalled 2016 vote, recalled 2020 vote, and 2024 vote intention, using the same Model 1 demographic specification throughout. An initial reading of these unbalanced estimates suggests the rural-city gap has narrowed modestly: the rural AME was 22.36 percentage points in 2016 (95% CI: 20.97–23.76), declined to 20.57 points in 2020 (95% CI: 19.19–21.96), and fell further to 18.97 points in 2024 (95% CI: 17.55–20.38).

However, this apparent narrowing does not survive a more demanding test. Because each year-specific sample includes only respondents with valid vote recall for that election, the three unbalanced samples are not identical in composition. To assess whether the over-time pattern reflects genuine change or differential non-response, the analysis was repeated on a balanced sample restricted to the 66,922 respondents with valid major-party vote recall in all three elections. On this common sample, the rural AME is essentially flat: 22.21 percentage points in 2016 (95% CI: 20.80–23.63), 22.12 in 2020 (95% CI: 20.70–23.54), and 22.10 in 2024 (95% CI: 20.64–23.55), as shown in Table 3. H2 is therefore supported: among consistent major-party voters, the geographic gap has remained relatively stable across the three

Figure 2: **Geographic AME on Trump Vote, 2016–2024**



Note: Points are average marginal effects in percentage points relative to city residents, estimated using Model 1 specifications (race, education, age, gender, income). Lines connect estimates for each geographic category across election cycles; vertical bars are 95% confidence intervals. Each year uses the maximum valid sample for that election (unbalanced): $N = 71{,}622$ (2016), 81,378 (2020), 84,837 (2024). 2024 measure uses pre-election vote intention, 2016 and 2020 estimates are based on recalled vote.

Trump-era elections. A pooled model stacking all three election years and clustering standard errors by respondent confirms this formally: the interaction between rural residence and election year (2024 versus 2016) is substantively negligible and statistically indistinguishable from zero ($\hat{\beta} = -0.014$ (log-odds), $p = 0.545$).

It is important to note that the differential non-response driving the apparent narrowing is geographically structured. Of the 17,915 respondents in the 2024 sample who are excluded from the balanced panel, the majority lack valid 2016 major-party recall: 50.8 percent were non-voters in 2016, 25.3 percent voted for a third-party candidate, and 13.5 percent were too young to have been eligible. Critically, this exclusion falls disproportionately on city residents, who have a retention rate of 74.2 percent, compared to 78.7 percent for town,

Table 3: **Rural AME on Trump Vote: Unbalanced vs. Balanced Panel, 2016–2024**

	Rural AME (pp)		
Sample	2016	2020	2024
Unbalanced	22.36***	20.57***	18.97***
	[20.97, 23.76]	[19.19, 21.96]	[17.55, 20.38]
	n = 71,622	n = 81,378	n = 84,837
Balanced	22.21***	22.12***	22.10***
	[20.80, 23.63]	[20.70, 23.54]	[20.64, 23.55]
		n = 66,922 (common sample)	

Note. Entries are average marginal effects in percentage points for the rural–city contrast, with 95% confidence intervals in brackets. All models use the Model 1 specification (race, education, age, gender, income). The unbalanced estimates use the maximum valid sample for each election year. The balanced estimates restrict to respondents with valid major-party vote recall in all three elections. The 2016 and 2020 entries are based on recalled vote reported in October 2024; the 2024 entry is based on pre-election vote intention. Survey weights applied. ***$p < .001$.

80.2 percent for rural, and 81.5 percent for suburban respondents. Because these city-skewing dropouts are included in the 2024 unbalanced sample but absent from the 2016 one, their presence in the later estimates artificially compresses the rural-city gap, producing the appearance of convergence where none exists among long-run major-party voters. This pattern is consistent with Trump's documented gains among previously non-voting urban working-class voters in 2024, a group that enters the 2024 sample without a comparable prior-election anchor. Full breakdowns of exclusion reasons by election year and retention rates by geographic category are reported in Appendix F.

5.4 Does the Gap Vary by Race and Education? (H3)

Table 4 displays geographic AMEs estimated separately for three mutually exclusive groups: white non-college respondents (n = 31,358), white college respondents (n = 37,947), and non-white respondents (n = 15,532). The racial dimension of H3 is confirmed: the rural AME is substantially larger among white voters—19.35 percentage points among non-college whites (95% CI: 17.29–21.41) and 22.52 percentage points among college whites (95% CI: 20.48–24.57)—than among non-white voters, where the rural gap is 13.36 percentage points

(95% CI: 9.77–16.94). The white-non-white contrast is large and the confidence intervals do not overlap, consistent with the expectation from Brown et al. (2025) and Teigen et al. (2017) that racial linked fate mutes geographic community effects for minority voters.

Within the white electorate, however, the education gradient runs opposite to the Cramer (2016) prediction. The rural AME is larger among college-educated white voters (22.52 pp) than among non-college white voters (19.35 pp), a difference of 3.17 percentage points that is statistically significant ($p = 0.032$). H3 is therefore partially supported: race moderates the geographic gap in the predicted direction, but education does not. The reversal of the expected education gradient suggests that the rural-urban political divide is not straightforwardly a working-class phenomenon; a further interpretation is taken up in Section 6.

Table 4: **Geographic AME on Trump Vote by Race-Education Subgroup, 2024**

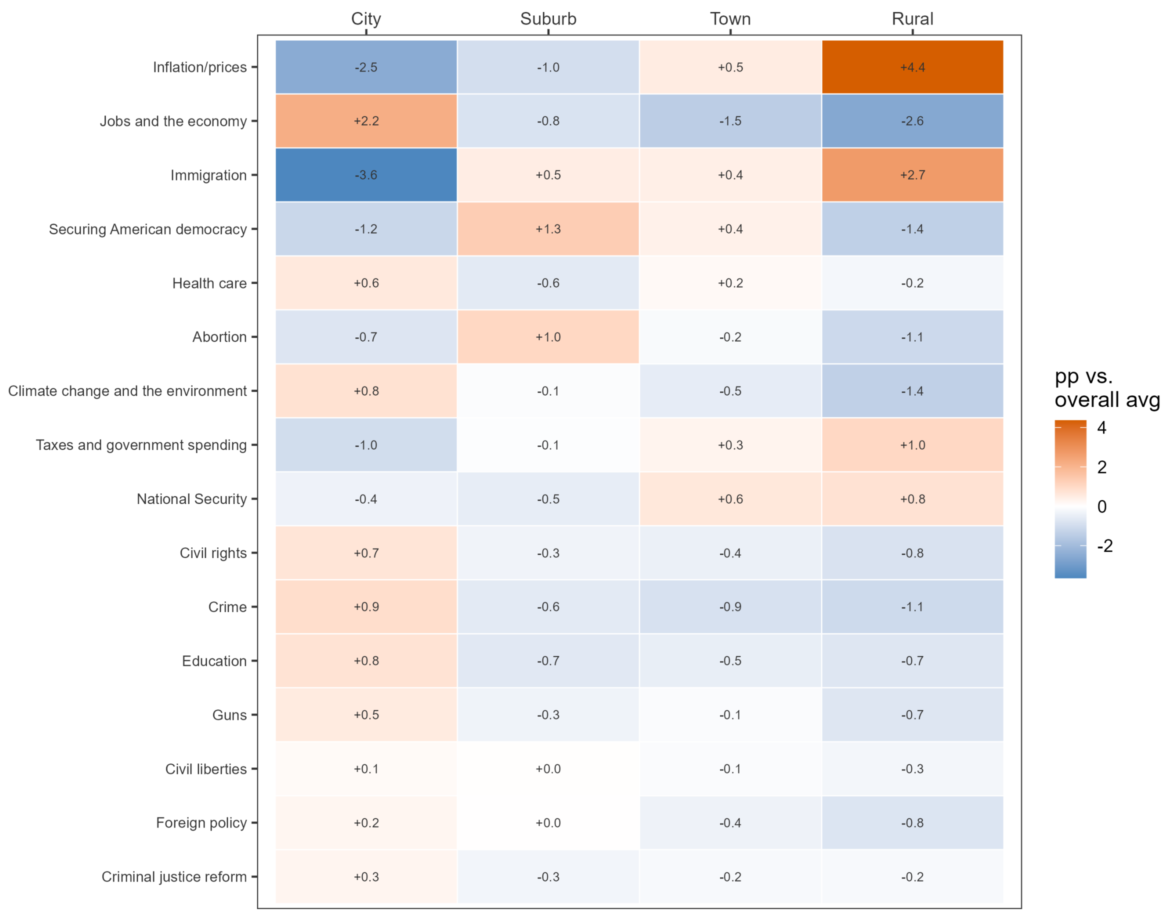
	Average Marginal Effect (pp)		
Contrast (vs. City)	White Non-College	White College	Non-White
Suburb	4.57***	9.96***	3.14**
	[2.46, 6.68]	[8.35, 11.57]	[0.76, 5.52]
Town	10.85***	12.51***	9.78***
	[8.43, 13.27]	[10.26, 14.76]	[6.05, 13.52]
Rural	19.35***	22.52***	13.36***
	[17.29, 21.41]	[20.48, 24.57]	[9.77, 16.94]

Note. Entries are average marginal effects in percentage points with 95% confidence intervals in brackets; City is the reference category. Models estimated using the Model 1 specification, stratified by subgroup. White non-college: non-Hispanic white respondents without a bachelor's degree ($n = 31{,}358$); White college: non-Hispanic white respondents with a bachelor's degree or higher ($n = 37{,}947$); Non-white: all non-Hispanic non-white respondents ($n = 15{,}532$). White subgroup models control for age, gender, and income; non-white model additionally controls for race and education. Survey weights applied. $^{**}p < .01$, $^{***}p < .001$.

5.5 Mediation Analysis

The mediation analysis rests on an empirical assumption that the data confirms: rural and urban voters do prioritize systematically different issues. Rural respondents are 6.8 percentage points more likely than city respondents to name inflation/prices as the most important problem facing the country and 6.4 percentage points more likely to name immigration. City respondents are 4.8 percentage points more likely to identify jobs and the economy as the most important issue, and 2.2 percentage points more likely to prioritize climate change. Figure 3 visualizes these patterns as deviations from the overall sample mean, highlighting where each geographic group diverges from the average.

Figure 3: **Issue Prioritization by Community Type, 2024**



Note: Heatmap cells display the percentage-point deviation from the overall survey-weighted sample mean in responses to the most-important-problem (MIP) question, which asks respondents to identify the single most important problem facing the country from a list of sixteen options. Positive values (orange) indicate higher-than-average prioritization; negative values (blue) indicate lower-than-average. Survey-weighted; $N = 84{,}698$ (respondents with valid MIP responses).

Table 5 presents the mediation results. Because each mediator is available for a different subset of respondents due to item non-response, baseline geographic effects are re-estimated on each analytic subsample before each mediator is introduced. Issue salience attenuates the rural AME by 4.61 percentage points (a 24 percent reduction); gun ownership by 5.11 percentage points (28 percent); and immigration attitudes by 5.45 percentage points (29 percent). Climate attitudes produce the largest single-mediator attenuation of 11.67 percentage points (62 percent), suggesting that rural-urban divergence in climate prioritization is the strongest issue-based channel through which place shapes the vote. When all four mediators are included simultaneously, the rural AME falls by 13.96 percentage points (76 percent). The remaining 24 percent of the geographic effect not accounted for by these four mediators points to additional community-level channels through which place shapes political behavior. These are discussed further in Section 6.

Table 5: **Geographic AME on Trump Vote Before/After Mediator Controls, 2024**

Model	Rural AME (pp)	95% CI	Attenuation
Panel A: Issue salience subsample			
Baseline (Model 1)	18.97***	[17.55, 20.38]	—
Model 4a: + Issue salience (MIP)	14.36***	[13.05, 15.67]	−24%
Panel B: Gun ownership subsample			
Baseline (Model 1)	18.49***	[17.03, 19.95]	—
Model 4b: + Gun ownership	13.38***	[11.90, 14.86]	−28%
Panel C: Immigration attitudes subsample			
Baseline (Model 1)	18.99***	[17.57, 20.41]	—
Model 4c: + Immigration attitudes	13.54***	[12.18, 14.90]	−29%
Panel D: Climate attitudes subsample			
Baseline (Model 1)	18.81***	[17.36, 20.27]	—
Model 4d: + Climate attitudes	7.14***	[5.82, 8.46]	−62%
Panel E: All four mediators subsample			
Baseline (Model 1)	18.39***	[16.89, 19.89]	—
Model 4e: + MIP + Gun + Imm + Cli	4.43***	[3.20, 5.67]	−76%

Note. Entries are average marginal effects in percentage points for the rural–city contrast, with 95% confidence intervals in brackets. Baseline models re-estimate the Model 1 specification (race, education, age, gender, income) on each mediator's analytic subsample; subsamples differ because each mediator is available for a different set of respondents due to item non-response. Subsample sizes are reported in Table A2 of Appendix A. Attenuation is the percentage reduction in the rural AME relative to the respective baseline. Survey weights applied. $^{***}p < .001$.

5.6 Robustness Checks

The main finding—a robust rural-city gap of approximately 19 percentage points in Trump vote choice after demographic controls—is stable across ten alternative specifications, which are reported in full in Appendix D. Several checks are particularly noteworthy. The results are consistent when an objective measure of geographic context replaces the self-reported community-type variable: using Census ZCTA population density, the estimated rural effect is 12.34 percentage points (RC5), confirming that the finding is not an artifact of subjective geographic self-classification.[2] The geographic effect also survives the inclusion of state fixed effects, which absorb all state-level variation in political culture, candidate strategy, and election administration: the rural AME under state fixed effects is 17.25 percentage points (RC6), confirming that the geographic gap is a within-state phenomenon, not merely a reflection of rural states leaning Republican. The effect is consistent across pre-election vote intention and post-election reported vote (18.03 pp, RC3), confirming that measurement timing does not drive the finding. As expected from the racial heterogeneity literature reviewed in Section 2, the geographic effect is largest among white respondents (20.40 pp, RC9), somewhat smaller but statistically significant among Hispanic respondents (14.32 pp), and substantially smaller among Black respondents (6.75 pp, $p = .028$), consistent with the theoretical expectation that linked fate moderates the place effect for minority voters. A list of all robustness check results is reported in Appendix D.

6 Discussion

This paper set out to test whether geographic context independently shapes presidential vote choice after controlling for individual demographic characteristics, and whether that effect varies across elections, racial groups, and education levels. The core findings are largely

[2] The smaller magnitude under RC5 reflects the continuous parameterization of geographic context rather than a weakening of the effect; density captures a different dimension of geographic variation than the categorical self-report.

consistent with a contextual account of geographic polarization: a large and robust rural-city gap persists after controlling for individual demographics, holds stable across all three Trump-era elections, and is substantially larger among white voters than non-white voters. One result, however, runs counter to the theoretical prediction: college-educated white rural voters exhibit a slightly larger geographic gap than non-college whites, a reversal that challenges the working-class framing that has dominated accounts of rural political realignment. This discussion interprets these patterns in turn, connects them to the theoretical mechanisms through which place shapes partisan identity, and draws out their implications for understanding the structural character of America's geographic political divide.

6.1 The Reality and Pathway of Geographic Contextual Effects

The most important finding of this paper is also the most straightforward: geographic context independently predicts presidential vote choice in a way that cannot be attributed to individual demographic composition. A rural voter and a city voter who share the same race, education, income, age, and gender differ by nearly 19 percentage points in their probability of voting for Trump, a large and substantial effect. Importantly, the individual-level design employed here cannot be explained away by the ecological inference problem that limits county-level studies: these are individual respondents, individually matched on their own demographic characteristics, who still vote differently depending on where they live.

The near-complete attenuation of the geographic effect under Model 3 is equally important, and the two findings together tell a coherent theoretical story. The reduction of the rural AME by 93 percent suggests that geography does not push voters directly toward Trump independently of their partisan and ideological identities; rather, geography appears to shape those identities themselves, and the identities then determine vote choice. In other words, place helps form the partisan.

This interpretation is consistent with a broader body of research on social networks and political socialization. Gimpel et al. (2020) find that the geographic gap in *party identification* (not just vote choice) is large, durable, and independent of demographics: the path runs from community context to partisan identity to vote choice, with community context doing its primary work at the identity-formation stage rather than the ballot-casting stage. In their social communication model, Huckfeldt and Sprague (1995) demonstrate that the political character of the local community shapes partisan preferences over time through repeated social interaction with neighbors, coworkers, and community contacts who transmit political cues reinforcing the dominant partisan position of the place. Huckfeldt (2014) extend this by showing that personal network ties and the broader community partisan context mutually amplify one another's influence, a dynamic especially powerful in the politically homogeneous communities rural areas have become. Enos (2017) adds that physical residential separation limits cross-group contact and deepens place-based political identities, making the social world of daily life an increasingly self-reinforcing partisan environment. Tonin et al. (2025) confirm this at scale, finding that physical co-location with co-partisans explains 97 percent of county-level presidential vote-share variance, outperforming even online partisan network ties. These studies, along with my findings, demonstrate that the geographic effect on the vote is not a short-term or campaign-specific phenomenon but the downstream electoral manifestation of longer-run processes of partisan identity formation in place-differentiated communities.

6.2 The Issue Mechanism: What Mediates and Why

Beyond socialization, the mediation results presented in Section 5.5 provide an additional, quantifiable answer to the question of how place translates into vote choice. The pattern is not coincidental: gun ownership, immigration, and climate are not arbitrary issues but the specific policy domains in which two conditions are simultaneously satisfied.

First, rural and urban communities have differential material exposure to the stakes of these policies. Gun ownership is substantially more prevalent in rural communities, where firearms are part of everyday life through hunting, recreation, and self-defense, making Second Amendment concerns a lived personal stake in a way they are not for otherwise identical urban voters. Importantly, Joslyn (2025) confirms this pattern explains a substantial portion of the rural-urban divide in Trump vote choice. Climate and energy regulation carry direct material consequences for communities economically dependent on fossil fuel extraction, agricultural production, and land use, such that rural and urban voters may differ not in their abstract valuation of the environment but in how personally costly they perceive climate policy to be. Immigration's salience is similarly grounded in local exposure, as rural communities that have experienced rapid demographic change through agricultural labor markets encounter immigration as a concrete feature of daily life rather than a distant national abstraction. Borwein et al. (2025) confirm that gun control and immigration are precisely the domains of greatest urban-rural policy disagreement, and find no evidence this disagreement has grown over time. This finding suggests it is the electoral activation of pre-existing geographic differences in material exposure, not growing substantive divergence, that drives the issue-based component of the vote gap.

Second, these domains also happen to be the policy areas on which the two parties are most sharply differentiated, meaning that geographic variation in salience maps almost directly onto vote choice. The implication is that the issue-based component of the geographic vote gap is not generated by fundamentally different underlying values across communities, but by the systematic coincidence of differential material exposure and maximum partisan differentiation in the same set of policy domains. Importantly, this combination does not require rural and urban voters to want different things from government, only that different things are at stake for them where they live.

The remaining 24 percent of the geographic effect that persists after all four mediators are controlled most plausibly reflects the mechanisms SAY24 does not directly measure: the place-based social networks that Tonin et al. (2025) document, the nationalized information environment produced by local news decline that Moskowitz (2021) identifies as a driver of partisan voting, and the place-based identity and resentment documented by Cramer (2016) and Jacobs and Munis (2023).

6.3 The Durability of the Geographic Divide

The balanced panel analysis establishes that the structural geographic gap has not changed meaningfully across the three Trump-era elections. This stability is a substantively important finding. If the mechanisms through which place shapes political behavior are long-run structural features of communities rather than conditional responses to any particular campaign, then the geographic gap in vote choice should be durable rather than election-specific. H2 is supported precisely because the data reflect this structure: among voters with a consistent record of major-party participation, geography appears to produce the same large, stable alignment across all three elections. This is also consistent with what Lunz Trujillo and Lin (2025) find at the attitudinal level: urban and rural residents do not differ systematically on abstract political values, but differ substantially when place identity rather than residence is the predictor. The divide is not one of genuinely different values but of identity and social reinforcement, which is precisely why it is durable.

The apparent narrowing in the unbalanced year-specific estimates is instead an artifact of the compositional differences between those samples, and interpreting it correctly is itself theoretically informative. The respondents excluded from the balanced panel are predominantly city residents who did not vote for a major-party candidate in 2016, whose entry into the 2024 Trump electorate reflects the well-documented urban working-class shift toward Trump in 2024. Their inclusion in the 2024 unbalanced sample but absence from the 2016 one mechanically compresses the rural-city gap, producing the appearance of convergence where none exists among long-run major-party voters. This is a feature of the 2024 electoral landscape, not a methodological error, but it means the unbalanced estimates are not measuring the same quantity across years. The stable gap among consistent major-party voters and the narrowing gap in the unbalanced analysis are not in tension: they are measuring different things.

Additionally, in tracing the rural-urban political divide from 1976 to 2020, Brown and Mettler (2024), find that the cleavage developed in sequential phases and accelerated most sharply in the decade before 2016, suggesting that the Trump elections consolidated a structural realignment already well underway rather than initiating it. This conclusion further supports the interpretation of the geographic gap as a durable feature of the electoral landscape rather than a situational one.

6.4 The Education Reversal and the Limits of the Working-Class Account

The H3 results reveal a striking and theoretically consequential pattern, as the racial dimension of the hypothesis is confirmed but the education dimension is not. The racial finding aligns with the prediction derived from Dawson (1994)'s theory of linked fate: for Black and other minority voters, racial group identity provides a powerful cross-cutting political identity that competes with geographic community as a source of partisan alignment, muting the influence of place-based mechanisms. The finding thus has a clear theoretical interpretation: geographic community effects are strongest when no comparably strong group identity competes with place as a source of partisan identity.

Within the white electorate, however, the education gradient runs opposite to the prediction derived from Cramer (2016)'s account of rural consciousness as a distinctively working-class phenomenon. If geographic context effects were concentrated among non-college whites for whom working-class place-based identity is theorized to operate with particular force, the education gradient should run in the opposite direction.

One theoretically plausible interpretation of this reversal involves selective retention into the white college rural category. Educated individuals who remain in or choose to settle in rural communities, rather than migrating to cities as educational attainment typically predicts, may be systematically different from their urban college-educated counterparts in ways that produce strong place-based political identity: they are more embedded in the local social fabric, more likely to own rural property and businesses, and more materially invested in the issues that align rural interests with the Republican Party. In this interpretation, the college-educated rural voter is not a theoretical anomaly but a case of extreme place-based identity formation, precisely because the decision to remain in a rural community involves a degree of local commitment that urban college graduates do not exhibit. Jacobs and Munis (2023)'s three-component measure of place-based resentment (economic, representational, and cultural) is, on this account, at least as characteristic of educated rural residents as of working-class ones, a possibility their quantitative evidence does not rule out. Experimental evidence from Jacobs and Munis (2019), demonstrating that place-based imagery independently shifts voter evaluations of candidates through psychological pathways distinct from policy preferences, further suggests that the salience of rural identity is not bounded by educational attainment. The broader implication is that the rural-urban political divide is not reducible to a class story: it is a place story, and education does not immunize rural residents from the community-level social and identity forces that the mechanisms in Section 3 describe.

Taken together, the three sets of findings point toward a common interpretation: America's urban-rural political divide is structural, identity-based, and durable—and it is unlikely to narrow significantly in the absence of changes to the community-level environments that sustain it. The gap is structural in the sense that it is not a statistical artifact of demographic composition and does not simply reflect the behavior of any particular demographic group; it reflects something about the communities themselves that shapes political behavior above the level of the individual. It is identity-based in the sense that geography exerts its primary influence through the partisan and ideological identities that place-based living helps to form, and it is durable in the sense that, among consistent major-party voters, the geographic gap has not changed meaningfully across three presidential elections.

7 Conclusion

This paper set out to answer a deceptively simple question: do voters with identical demographic profiles vote differently depending on where they live? The answer, based on 84,837 respondents from the October 2024 SAY24 baseline, is yes. After controlling for race, education, income, age, and gender, rural residents are nearly 19 percentage points more likely to vote for Trump than demographically identical city residents, a gap that survives additional controls and has remained essentially flat across all three Trump-era elections. The gap is substantially larger among white voters than non-white voters, consistent with racial linked fate providing a competing political identity that weakens place-based mechanisms, but runs opposite to the working-class account within the white electorate: college-educated rural whites exhibit a slightly larger geographic gap than non-college whites. This finding points toward a selective-retention interpretation in which place-based identity operates with intensified force among educated individuals who remain embedded in rural communities. Issue-based channels account for approximately 76 percent of the rural effect, with partisan identity accounting for nearly all of it, suggesting that place shapes the vote primarily through long-run partisan identity formation rather than direct, election-specific effects.

7.1 Implications for Theory and Practice

These results hold important implications for both scholarly understanding and normative conceptions of the rural-urban divide. First, this paper extends the foundational individual-level evidence of Gimpel et al. (2020) from party identification to vote choice and from a single survey wave to the full 2016–2024 period, confirming that the geographic contextual effect is large and has persisted across all three elections in which Trump appeared on the presidential ballot. Second, it establishes that despite conventional accounts, the rural-urban gap has remained consistent across the Trump-era elections. Third, it provides the first formal empirical test at this scale of whether issue-based differences partially mediate the geographic effect on vote choice, identifying climate attitudes as the single largest mediating channel and establishing that the mechanisms posited by the theoretical literature are empirically operative.

What do these findings mean for where the geographic divide goes from here? The stability of the gap across the Trump era is not reassuring in the way it might first appear. A stable 22-point divide among consistent voters does not suggest convergence; it suggests that the structural conditions sustaining the divide are not eroding. The more pointed question is whether these conditions are specifically tied to the Trump political moment or are features of rural community life that will persist regardless of who leads the Republican Party. If the gap is primarily a product of the partisan and ideological identities that place-based living has helped form over time, then it will not narrow simply because Trump is no longer on the ballot; the identities he consolidated were formed in communities that existed long before his candidacy and will continue to shape political behavior after it. The more plausible scenario for narrowing would require changes to the community-level environments that sustain the divide: the reconstruction of cross-cutting social contacts eroded by residential sorting, or the reduction of the material exposure gaps in energy, trade, and immigration that make different policy questions salient in different places. None of these changes are imminent, which suggests that America's geographic political divide is likely to remain a durable feature of the electoral landscape for the foreseeable future.

7.2 Limitations and Future Research

While the findings of this paper offer valuable insights, several limitations warrant consideration and suggest important directions for future research. First, the mediation analysis is observational rather than causal. Future research designs exploiting natural variation in issue exposure across communities, such as regulatory shocks that shift energy policy salience for extraction-dependent areas, or trade policy changes that differentially affect agricultural versus manufacturing communities, would allow for sharper causal inference about which issue channels drive the geographic effect. Second, the over-time comparisons rest on retrospective recall rather than a true longitudinal panel, leaving open the question of whether geographic context predicts within-person change in partisan identity over time. A multi-wave panel tracking the same voters across elections would allow for a direct test of the identity-formation pathway that the current Model 3 results imply but cannot confirm. Third, and most consequentially, the 24 percent of the rural AME that persists after all four issue-based mediators are controlled points to mechanisms SAY24 does not measure, such as social network composition and place-based resentment. A large-scale survey that incorporated these items alongside SAY24's existing coverage would allow for a near-complete decomposition of the geographic effect into its theoretical components, and would move the literature substantially closer to a fully specified causal account of how place shapes political behavior in contemporary American democracy.

In sum, this paper provides new individual-level evidence that America's geographic political divide is structural rather than demographic, stable rather than accelerating, and sustained by the community-level environments in which voters form their partisan identities. The findings suggest that narrowing the divide would require not merely different candidates or campaigns, but changes to the social and material conditions of place-differentiated communities that have accumulated over decades. Where people live shapes who they politically become, and these results suggest that relationship is unlikely to dissolve on its own.

References

Albrecht, D. E. (2022). Donald Trump and changing rural/urban voting patterns. *Journal of Rural Studies*, *91*, 148–156. https://doi.org/10.1016/j.jrurstud.2022.03.009

Borwein, S., Lucas, J., Romualdi, T., Taylor, Z., Armstrong, D. A., & McCoy, K. (2025). Urban–rural policy disagreement. *European Journal of Political Research*, *64*(4), 1827–1848. https://doi.org/10.1111/1475-6765.70009

Brown, T. D., Jauregui, G. P., Mettler, S., & Rivera, M. (2025). A rural-urban political divide among whom? Race, ethnicity, and political behavior across place. *Politics, Groups, and Identities*, *13*(1), 229–242. https://doi.org/10.1080/21565503.2024.2328551

Brown, T. D., & Mettler, S. (2024). Sequential polarization: The development of the rural-urban political divide, 1976–2020. *Perspectives on Politics*, *22*(3), 630–658. https://doi.org/10.1017/S1537592723002918

Cramer, K. J. (2016). *The politics of resentment: Rural consciousness in Wisconsin and the rise of Scott Walker*. University of Chicago Press.

Dawson, M. C. (1994). *Behind the mule: Race and class in african-american politics*. Princeton University Press.

Enos, R. D. (2017). *The space between us: Social geography and politics*. Cambridge University Press.

Gimpel, J. G., Lovin, N., Moy, B., & Reeves, A. (2020). The urban–rural gulf in American political behavior. *Political Behavior*, *42*(4), 1343–1368. https://doi.org/10.1007/s11109-020-09601-w

Huckfeldt, R. R. (2014). Networks, contexts, and the combinatorial dynamics of democratic politics. *Political Psychology*, *35*(S1), 43–68. https://doi.org/10.1111/pops.12161

Huckfeldt, R. R., & Sprague, J. (1995). *Citizens, politics, and social communication: Information and influence in an election campaign*. Cambridge University Press.

Jacobs, N. F., & Munis, B. K. (2019). Place-based imagery and voter evaluations: Experimental evidence on the politics of place. *Political Research Quarterly*, *72*(2), 263–277. https://doi.org/10.1177/1065912918781035

Jacobs, N. F., & Munis, B. K. (2023). Place-based resentment in contemporary U.S. elections: The individual sources of America's urban–rural divide. *Political Research Quarterly*, *76*(3), 1102–1118. https://doi.org/10.1177/10659129221124864

Joslyn, M. R. (2025). Gun ownership: The bridge between rural and urban voters in 2020. *Social Science Quarterly*, *106*(3). https://doi.org/10.1111/ssqu.70016

Lunz Trujillo, K., & Lin, J. (2025). Real or imagined? American urban–rural differences in political values. *Political Research Quarterly*, *78*(3), 849–859. https://doi.org/10.1177/10659129251324464

Martin, G. J., & Webster, S. W. (2020). Does residential sorting explain geographic polarization? *Political Science Research and Methods*, *8*(2), 215–231. https://doi.org/10.1017/psrm.2018.44

Moskowitz, D. J. (2021). Local news, information, and the nationalization of U.S. elections. *American Political Science Review*, *115*(1), 114–129. https://doi.org/10.1017/S0003055420000829

Pautonnier, V., Dassonneville, R., Lewis-Beck, M. S., & Nadeau, R. (2026). The rural–urban cleavage in US presidential elections: Stability and sudden change. *Electoral Studies*, *99*. https://doi.org/10.1016/j.electstud.2025.103019

Rodden, J. A. (2019). *Why cities lose: The deep roots of the urban–rural political divide*. Basic Books.

Scala, D. J., & Johnson, K. M. (2017). Political polarization along the rural–urban continuum? The geography of the presidential vote, 2000–2016. *The ANNALS of the American Academy of Political and Social Science*, *672*(1), 162–184. https://doi.org/10.1177/0002716217712696

Shepherd, M. E. (2025). *Diploma divide, rural revolt, or racial realignment? The working-class voter in the Trump era* [Paper presented at the State of the Parties Conference, University of Akron, https://www.uakron.edu/bliss/docs/2025-State-of-the-Parties/shepherd-sop25-paper.pdf].

Stanford University, Arizona State University, and Yale University. (2024). Stanford-arizona state-yale 2024 election study (SAY24) [Restricted-access dataset. Data collected by YouGov. October 2024 baseline wave used in this analysis.].

Teigen, J. M., Shaw, D. R., & McKee, S. C. (2017). Density, race, and vote choice in the 2008 and 2012 presidential elections. *Research Politics*, *4*(2). https://doi.org/10.1177/2053168017702989

Tonin, M., Lepri, B., & Tizzoni, M. (2025). Physical partisan proximity outweighs online ties in predicting US voting outcomes. *PNAS Nexus*, *4*(10). https://doi.org/10.1093/pnasnexus/pgaf308

Wilkinson, W. (2019). The density divide: Urbanization, polarization, and populist backlash. https://www.niskanencenter.org/wp-content/uploads/2019/09/Wilkinson-Density-Divide-Final.pdf

Appendix

Same People, Different Places: Geographic Context and Vote Choice in the Trump Electorate

Jessica Persano

This appendix contains supplementary materials for the main analysis, including sample construction details, variable coding and operationalization, formal model specifications, robustness checks, full logistic regression coefficients, and balanced panel decomposition.

Appendix A: Sample Construction and Attrition

Table A1 documents the sequential exclusions applied to the SAY24 October 2024 baseline to arrive at the primary analysis sample of 84,837 respondents.

Table A1: **Sample Construction and Attrition**

Exclusion criterion	N excluded	N remaining
SAY24 October 2024 baseline	—	109,255
Exclude "other" or missing community type	933	108,322
Exclude missing survey weight	0	108,322
Exclude missing demographic controls	13,003	95,319
Exclude non-voters, third-party, and undecided	10,482	84,837
Primary analysis sample		84,837

Note. The table traces the sequential exclusions applied to the SAY24 October 2024 baseline (N = 109,255) to arrive at the primary analysis sample (N = 84,837). Missing demographic controls include missing values on income, education, age, gender, and race. Robustness check RC1 retains non-voters, third-party voters, and undecided; see Appendix D.

Table A2 reports the number of respondents available for each mediator subsample used in the mechanism analysis (Section 5.5).

Table A2: **Mediator Subsample Sizes**

Model	Mediator	N	% of primary sample
Primary sample	—	84,837	100.0
Model 4a	Most important problem (MIP)	84,698	99.8%
Model 4b	Gun ownership	81,376	95.9%
Model 4c	Immigration attitudes	84,616	99.7%
Model 4d	Climate attitudes	79,996	94.3%
Model 4e	All four mediators	76,576	90.3%

Note. N is the number of respondents in the primary sample (N = 84,837) with a valid (non-missing) response on the mediator variable(s) for that model. Subsamples differ because each mediator question is available for a different set of respondents due to item non-response.

Appendix B: Variable Coding and Operationalization

Table B1 describes the coding and operationalization of the variables used in the present analyses.

Table B1: **Variable Coding and Operationalization**

Variable	Coding	Categories / Range
Dependent variable		
Trump vote (2024)	Binary	1 = Trump; 0 = Harris
Trump vote (2020, recalled)	Binary	1 = Trump; 0 = Biden
Trump vote (2016, recalled)	Binary	1 = Trump; 0 = Clinton
Key independent variable		
Community type	4-category factor	City (ref.); Suburb; Town; Rural
Demographic controls (Models 1–3)		
Race/ethnicity	4-category factor	White (ref.); Black; Hispanic; Other
Education	4-category factor	HS or less (ref.); Some college; College grad; Postgrad
Age	4-category factor	Under 30 (ref.); 30–44; 45–64; 65+
Gender	Binary (numeric)	0 = Male; 1 = Female
Income	3-category factor	Under $50K (ref.); $50–100K; $100K+
Regional control (Models 2 and 3)		
Census region	4-category factor	Northeast (ref.); Midwest; South; West
Partisan identity controls (Model 3 only)		
Party identification	Numeric, 1–7	1 = Strong Democrat; 2 = Not very strong Democrat; 3 = Lean Democrat; 4 = Independent; 5 = Lean Republican; 6 = Not very strong Republican; 7 = Strong Republican
Ideological self-placement	Numeric, 1–5	1 = Very liberal; 2 = Liberal; 3 = Moderate; 4 = Conservative; 5 = Very conservative

Continued on next page

Table B1 continued

Variable	Coding	Categories / Range
Subgroup indicators (Section 5.4)		
White non-college	Binary (derived)	1 = non-Hispanic white without bachelor's degree; 0 = otherwise (n = 31,358)
White college	Binary (derived)	1 = non-Hispanic white with bachelor's degree or higher; 0 = otherwise (n = 37,947)
Non-white	Binary (derived)	1 = non-Hispanic non-white; 0 = otherwise (n = 15,532)
Mediating variables (Section 5.5)		
Most important problem	16-category factor	Inflation/prices (ref.); Jobs and the economy; Immigration; Securing American democracy; Health care; Education; Taxes and government spending; Foreign policy; National security; Climate change and the environment; Abortion; Civil rights; Civil liberties; Guns; Crime; Criminal justice reform
Gun ownership	Binary (numeric)	0 = Does not personally own a gun; 1 = Personally owns a gun
Immigration attitudes	Binary (numeric)	0 = Prefers same or increased immigration levels; 1 = Prefers decreased immigration levels
Climate attitudes	Binary (numeric)	0 = Prefers to do more to address climate change; 1 = Prefers to prioritize other issues over climate change

Note. All variables are from the SAY24 October 2024 baseline wave. Reference categories for factor variables are listed in parentheses; full response options are shown for each variable. Survey weights applied in all models.

Appendix C: Formal Model Specifications

This appendix presents the formal specification of every model estimated in the main analysis and robustness checks. All primary models use survey-weighted logistic regression via `svyglm()` with a `quasibinomial()` family. Throughout, i indexes respondents and $t \in \{2016, 2020, 2024\}$ indexes election years; $\text{geo}_i = (\text{Rural}_i, \text{Suburb}_i, \text{Town}_i)$ is a vector of geographic indicators with City as the omitted reference category; $\mathbf{X}_i$ is a vector of five demographic controls (race, educational attainment, age, gender, household income); Region_i is a vector of census region indicators with Northeast as the reference; $\text{Year}_t = (\text{Year2020}_t, \text{Year2024}_t)$ is a vector of election-year indicators with 2016 as the reference; PID_i is a seven-point party identification scale; Ideo_i is a five-point ideological self-placement scale; and M_i denotes a mediating variable.

C.1 Primary Cross-Sectional Models (H1)

Model 1 (primary specification):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i$$

Model 2 (adds census region):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \boldsymbol{\delta}'\text{Region}_i$$

Model 3 (adds party identification and ideology):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \boldsymbol{\delta}'\text{Region}_i + \alpha_1\text{PID}_i + \alpha_2\text{Ideo}_i$$

C.2 Over-Time Models (H2)

The over-time comparison re-estimates Model 1 separately for each election year $t \in \{2016, 2020, 2024\}$, where $\text{Trump}_{i,t}$ is respondent i's binary major-party vote for Trump in year t (recalled vote for 2016 and 2020; pre-election intention for 2024):

$$\text{logit}\big(\Pr(\text{Trump}_{i,t} = 1)\big) = \beta_{0,t} + \boldsymbol{\beta}_t'\text{geo}_i + \boldsymbol{\gamma}_t'\mathbf{X}_i \qquad t \in \{2016,\ 2020,\ 2024\}$$

The balanced-panel version applies the same specification to the subsample of respondents with valid major-party recall in all three elections ($N = 66{,}922$).

To formally test whether the rural gap changed across elections, a pooled model is estimated on the balanced panel in long format ($3 \times 66{,}922 = 200{,}766$ observation-years), with standard errors clustered by respondent via `ids = ~respondent_id`:

$$\text{logit}\big(\Pr(\text{Trump}_{i,t} = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\delta}'\text{Year}_t + \boldsymbol{\theta}'(\text{geo}_i \times \text{Year}_t) + \boldsymbol{\gamma}'\mathbf{X}_i$$

where $\boldsymbol{\theta}$ captures the full set of geo-by-year interaction coefficients. The primary quantity of interest is $\theta_{\text{Rural}\times\text{Year2024}}$, which tests whether the Rural–City gap in 2024 differs significantly from its 2016 baseline (H_0: $\theta_{\text{Rural}\times\text{Year2024}} = 0$).

C.3 Subgroup Models (H3)

The H3 analysis re-estimates Model 1 within three mutually exclusive strata. Race and education controls are omitted within white strata (constant by construction); the non-white model retains all demographic controls.

White non-college and **White college** strata:

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \gamma_1\text{Age}_i + \gamma_2\text{Female}_i + \gamma_3\text{Income}_i$$

Non-white stratum:

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i$$

C.4 Mechanism Models

Each mechanism model is estimated on the subsample for which mediator M is available. A within-sample baseline (Model 1 on the same subsample) is estimated first; the attenuation in the rural AME upon adding M is the quantity of interest.

Models 4a–4d (single mediator, where M_i is issue salience, gun ownership, immigration attitudes, or climate attitudes, respectively):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \lambda M_i$$

Model 4e (all four mediators simultaneously):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \textstyle\sum_{k=1}^{4} \lambda_k M_{ki}$$

C.5 Robustness Checks (RC1–RC10)

All robustness checks use survey-weighted quasibinomial logistic regression via `svyglm()` unless noted. All reported quantities are average marginal effects on the probability of a Trump vote.

RC1 (Alternative DV: Trump vs. all others). The dependent variable is recoded so that $\tilde{Y}_i = 1$ if the respondent intends to vote Trump, and $\tilde{Y}_i = 0$ for all others (Harris, third-party candidates, non-voters, and undecided). The sample is expanded to include non-voters and third-party voters (N = 95,319). All other aspects of the Model 1 specification are unchanged:

$$\text{logit}\big(\Pr(\tilde{Y}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i$$

RC2 (Alternative DV: Multinomial vote choice). The dependent variable is expanded to four categories ($V_i \in \{\text{Harris, Trump, ThirdParty, NonVoter}\}$, with Harris as the baseline outcome; "Not sure" responses excluded). Estimated via `nnet::multinom()` with survey case weights applied:

$$\log \frac{\Pr(V_i = k)}{\Pr(V_i = \text{Harris})} = \beta_{0k} + \boldsymbol{\beta}_k' \text{geo}_i + \boldsymbol{\gamma}_k' \mathbf{X}_i, \qquad k \in \{\text{Trump, ThirdParty, NonVoter}\}$$

The reported AME is the Rural − City contrast on $\Pr(V_i = \text{Trump})$.

RC3 (Alternative DV: Post-election reported vote). The dependent variable is replaced with post-election reported presidential vote ($Y_i^{\text{post}} = 1$ if Trump, 0 if Harris) from the November 2024 SAY24 baseline ($N = 77{,}802$). All other aspects of the Model 1 specification are unchanged:

$$\text{logit}\big(\Pr(Y_i^{\text{post}} = 1)\big) = \beta_0 + \boldsymbol{\beta}' \text{geo}_i + \boldsymbol{\gamma}' \mathbf{X}_i$$

RC4 (Alternative geographic IV: Binary urban/rural). The four-category community type is collapsed to a binary indicator: $\text{geo2}_i = 0$ if City or Suburb ("Urban", reference) and $\text{geo2}_i = 1$ if Town or Rural ("Rural/Town"). The model is estimated on the primary sample ($N = 84{,}837$):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \beta_1 \text{geo2}_i + \boldsymbol{\gamma}' \mathbf{X}_i$$

The reported AME is Rural/Town − Urban.

RC5 (Alternative geographic IV: Census ZCTA population density). The categorical community type is replaced with log ZCTA population density $d_i = \log(\text{persons per km}^2)$, derived from Census ACS 2020 five-year estimates and linked to respondents by ZIP code. The model is estimated on the subsample with valid ZCTA density matches:

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \beta_1 d_i + \boldsymbol{\gamma}' \mathbf{X}_i$$

The AME of d_i is scaled by the mean Rural − City log-density difference (−3.415 ln units) to produce a Rural-City-equivalent estimate in percentage points.

RC6 (State fixed effects). State-level fixed effects are added to absorb all state-level variation in political culture, party strategy, and election administration. Let State_i denote a vector of 50 state indicators (estimated via `factor(inputstate)`):

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \boldsymbol{\alpha}'\text{State}_i$$

RC7 (Unweighted). Model 1 re-estimated without survey weights using standard binomial logistic regression via `glm()`:

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i$$

The right-hand side is identical to Model 1; the only change is the omission of survey weights.

RC8 (Education gradient within white voters). A geographic-by-education interaction is estimated within the white subsample. Race is omitted (constant = White); education enters both as a main effect and as an interaction with community type. Let Educ_i denote a vector of three education indicators (Some college, College grad, Postgrad; HS or less as reference) and $\boldsymbol{\theta}'$ the vector of geo $\times$ education interaction coefficients:

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0+\boldsymbol{\beta}'\text{geo}_i+\boldsymbol{\psi}'\text{Educ}_i+\boldsymbol{\theta}'(\text{geo}_i\times\text{Educ}_i)+\gamma_1\text{Age}_i+\gamma_2\text{Female}_i+\gamma_3\text{Income}_i$$

Conditional Rural AMEs are reported separately at each of the four education levels. The non-white pooled AME is taken directly from the H3 non-white stratum model (Section C.3).

RC9 (Racial subgroup models). Model 1 is estimated separately within White ($N = 69{,}305$), Black ($N = 5{,}686$), and Hispanic ($N = 5{,}254$) subsamples. Race is omitted (constant within each subgroup); all remaining Model 1 controls are retained. Let Educ_i, Age_i, Female_i, Income_i denote the remaining demographic controls:

$$\text{logit}\big(\Pr(\text{Trump}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\psi}'\text{Educ}_i + \gamma_1\text{Age}_i + \gamma_2\text{Female}_i + \gamma_3\text{Income}_i$$

Estimated separately for each racial subgroup via `svyglm()` with survey weights.

RC10 (Cross-wave stability). Model 1 is re-estimated in four weekly SAY24 waves (Weeks 28, 32, 36, and 40; July–October 2024) to test whether the main result is an artifact of the October 2024 baseline. The dependent variable in each wave is $Y_i^w = 1$ if the respondent intends to vote Trump and 0 if Harris, derived from `presvote24h` ($N \approx$ 4,100–4,300 per wave). The specification is identical to Model 1:

$$\text{logit}\big(\Pr(Y_i^w = 1)\big) = \beta_0 + \boldsymbol{\beta}'\text{geo}_i + \boldsymbol{\gamma}'\mathbf{X}_i$$

Estimated separately for each wave $w \in \{28, 32, 36, 40\}$.

Appendix D: Robustness Checks

The main analysis result—a rural-city gap of 18.97 percentage points in Trump vote choice after demographic controls—is examined through ten alternative specifications. Figure D1 and Table D1 report the rural AME and 95% confidence interval for each check.

Dependent variable alternatives (RC1–RC3). Recoding Trump vote as Trump-versus-all-others, including Harris voters, non-voters, and third-party voters, and undecided respondents, produces a rural AME of 13.55 percentage points (RC1). A multinomial logistic regression that models the full four-category vote outcome (Trump, Harris, third party, did not vote) yields a Trump-versus-Harris conditional contrast of 18.82 percentage points (RC2). Using post-election reported vote from the November 2024 wave rather than pre-election vote intention yields 18.03 percentage points (RC3), confirming that the finding is not specific to the pre-election measurement.

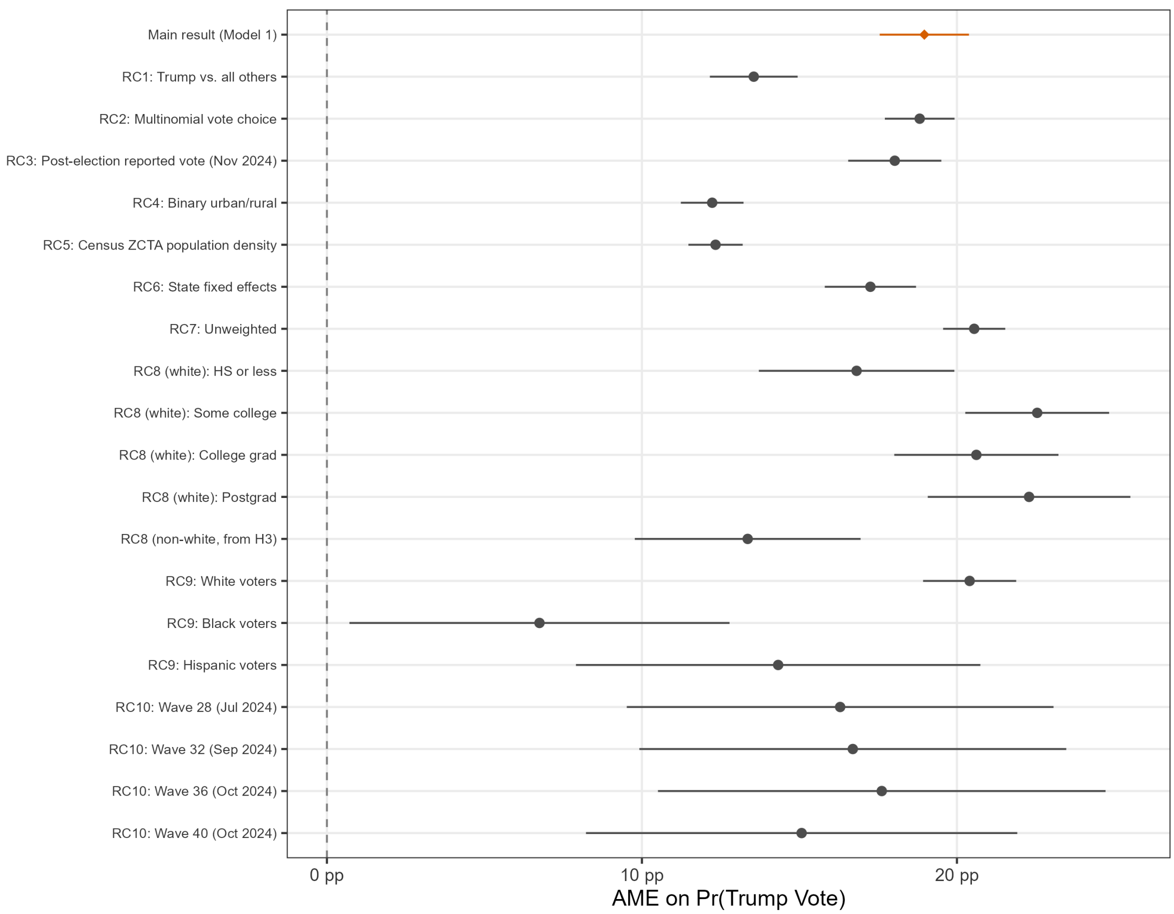
Geographic measure alternatives (RC4–RC5). A binary urban-versus-rural coding, which collapses cities and suburbs into an urban category and towns and rural areas into a rural category, yields a 12.23 percentage point effect (RC4). Replacing self-reported community type with Census Bureau population density at the ZCTA level yields a 12.34 percentage point effect (RC5), confirming that the geographic effect is not driven by subjective self-classification.

Model specification alternatives (RC6–RC7). Adding state fixed effects to the baseline Model 1 yields 17.25 percentage points (RC6), confirming that the geographic gap is a within-state phenomenon. Estimating the model without survey weights yields 20.55 percentage points (RC7), suggesting that weighting slightly attenuates the geographic effect.

Subgroup analyses (RC8–RC9). RC8 estimates a geography-by-education interaction within the white subsample, reporting rural AMEs separately for each education level; the gap ranges from 16.81 percentage points among white respondents with a high school education or less to 22.55 among those with some college, with the non-white estimate (13.36 pp) sitting clearly below all white education groups. Estimated separately within racial groups (RC9), the rural AME is 20.40 percentage points among white respondents, 14.32 percentage points among Hispanic respondents, and 6.75 percentage points among Black respondents, consistent with the expectation that racial group identity provides a cross-cutting anchor that attenuates the geographic effect among minority voters.

Cross-wave stability (RC10). Estimates from four separate weekly survey waves fielded between July and October 2024 range from 15.07 to 17.61 percentage points, all statistically significant and broadly consistent with the main result.

Figure D1: **Rural AME on Trump Vote Across Robustness Specifications**



Note: Forest plot of rural average marginal effects (vs. city residents) in percentage points across ten robustness specifications. Points are rural AMEs; horizontal bars are 95% confidence intervals. The orange diamond marks the main result from Model 1 (18.97 pp). RC5 (ZCTA population density) is scaled by the rural-city difference in log density to enable visual comparison with the categorical specifications. Formal specifications for all robustness checks are provided in Appendix C.

Table D1: **Rural AME on Trump Vote Across Robustness Specifications**

Specification	Rural AME (pp)	95% CI	N
Main result (Model 1)	18.97***	[17.55, 20.38]	84,837
Dependent variable alternatives			
RC1: Trump vs. all others	13.55***	[12.16, 14.94]	95,319
RC2: Multinomial vote choice	18.82***	[17.71, 19.92]	88,224
RC3: Post-election reported vote	18.03***	[16.55, 19.50]	77,802
Geographic measure alternatives			
RC4: Binary urban/rural	12.23***	[11.24, 13.23]	84,837
RC5: Census ZCTA population density	12.34***	[11.48, 13.20]	81,973
Model specification alternatives			
RC6: State fixed effects	17.25***	[15.81, 18.70]	84,837
RC7: Unweighted	20.55***	[19.56, 21.53]	84,837
Subgroup analyses			
RC8: Geography × education within white subsample (+ non-white)			
White: HS or less	16.81***	[13.71, 19.92]	8,663
White: Some college	22.55***	[20.26, 24.83]	22,695
White: College grad	20.62***	[18.01, 23.22]	21,273
White: Postgrad	22.29***	[19.07, 25.51]	16,674
Non-white	13.36***	[9.77, 16.94]	15,532
RC9: Racial subgroups			
White respondents	20.40***	[18.93, 21.88]	69,305
Black respondents	6.75*	[0.71, 12.78]	5,686
Hispanic respondents	14.32***	[7.91, 20.74]	5,254
Cross-wave stability (RC10)			
Wave 28 (Jul 2024)	16.29***	[9.52, 23.07]	4,269
Wave 32 (Sep 2024)	16.69***	[9.92, 23.47]	4,323
Wave 36 (Oct 2024)	17.61***	[10.51, 24.72]	4,202
Wave 40 (Oct 2024)	15.07***	[8.22, 21.92]	4,126

Note. Entries are average marginal effects of rural versus city in percentage points, with 95% confidence intervals in brackets. RC5 reports the rural AME scaled by the difference in mean log population density between rural and city ZCTAs (-3.415 ln units) to enable comparability. N is the sample size for each specification.$^{*}p < .05$, $^{***}p < .001$.

Appendix E: Full Logistic Regression Coefficients

Table E1 reports the full log-odds coefficients from the three logistic regression models estimated for H1. These are the underlying models from which the average marginal effects reported in Table 2 of the main text are derived.

Table E1: **Full Logistic Regression Coefficients on Trump Vote, 2024**

	Log-Odds Coefficient		
	Model 1 Demographics	Model 2 + Region	Model 3 + PID/Ideology
Geographic community type (ref: City)			
Suburb	0.267***	0.239***	−0.074
	[0.212, 0.321]	[0.184, 0.294]	[−0.194, 0.046]
Town	0.497***	0.485***	0.187*
	[0.426, 0.568]	[0.413, 0.557]	[0.031, 0.343]
Rural	0.851***	0.803***	0.240**
	[0.787, 0.915]	[0.739, 0.868]	[0.093, 0.387]
Race/ethnicity (ref: White)			
Black	−1.592***	−1.652***	−0.640***
	[−1.695, −1.490]	[−1.757, −1.548]	[−0.841, −0.439]
Hispanic	−0.485***	−0.480***	0.070
	[−0.568, −0.402]	[−0.564, −0.396]	[−0.112, 0.252]
Other	−0.421***	−0.391***	0.032
	[−0.504, −0.337]	[−0.475, −0.307]	[−0.142, 0.206]
Education (ref: HS or less)			
Some college	−0.494***	−0.492***	−0.412***
	[−0.554, −0.434]	[−0.553, −0.432]	[−0.544, −0.281]
College grad	−0.740***	−0.742***	−0.527***
	[−0.802, −0.678]	[−0.804, −0.680]	[−0.661, −0.393]
Postgrad	−1.123***	−1.126***	−0.704***
	[−1.189, −1.057]	[−1.193, −1.059]	[−0.848, −0.559]

Continued on next page

Table E1 continued

	Model 1 Demographics	Model 2 + Region	Model 3 + PID/Ideology
Age (ref: Under 30)			
30–44	0.134**	0.119*	−0.097
	[0.042, 0.226]	[0.026, 0.212]	[−0.292, 0.098]
45–64	0.373***	0.349***	−0.313***
	[0.289, 0.458]	[0.264, 0.434]	[−0.490, −0.136]
65+	0.441***	0.419***	−0.435***
	[0.357, 0.525]	[0.335, 0.503]	[−0.609, −0.260]
Gender (ref: Male)			
Female	−0.415***	−0.421***	−0.178***
	[−0.458, −0.373]	[−0.464, −0.378]	[−0.270, −0.086]
Income (ref: Under $50K)			
$50–100K	0.112***	0.120***	−0.133*
	[0.058, 0.166]	[0.066, 0.175]	[−0.250, −0.017]
$100K+	0.038	0.056	−0.251***
	[−0.018, 0.095]	[−0.001, 0.113]	[−0.373, −0.128]
Census region (ref: Northeast; Models 2 and 3)			
Midwest	—	0.186***	−0.026
	—	[0.119, 0.252]	[−0.162, 0.111]
South	—	0.400***	−0.052
	—	[0.339, 0.460]	[−0.188, 0.083]
West	—	−0.017	−0.264***
	—	[−0.085, 0.051]	[−0.413, −0.115]
Partisan identity (Model 3 only)			
Party ID (7-pt)	—	—	1.214***
	—	—	[1.177, 1.251]
Ideology (5-pt)	—	—	0.955***
	—	—	[0.888, 1.022]

Continued on next page

Table E1 continued

	Model 1 Demographics	Model 2 + Region	Model 3 + PID/Ideology
Intercept	0.262^{***}	0.114^{*}	-6.890^{***}
	[0.161, 0.364]	[0.005, 0.223]	[−7.204, −6.575]

Note. Entries are log-odds coefficients from survey-weighted logistic regression with quasibinomial variance estimation; 95% confidence intervals in brackets. City is the reference category for community type. Model 1 controls for race, education, age, gender, and income. Model 2 adds census region; Model 3 adds party identification (7-point scale) and ideological self-placement (5-point scale), retaining all prior controls. The intercept represents the log-odds of voting Trump for the reference category (city residents) at the reference levels of all other covariates. "—" indicates a term not included in that model. $N = 84{,}837$. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix F: Balanced Panel Decomposition

Tables F1 and F2 report the breakdown of the 17,915 respondents excluded from the balanced panel by their 2016 and 2020 vote recall status, respectively. Reasons for exclusion include non-participation in that election (non-voter or third-party voter), age ineligibility, or structural missingness in the recall variable.

Table F1: **Balanced Panel Exclusions by 2016 Vote Recall**

2016 Recall Status	*N*	% of Dropped
Non-voter 2016	9,098	50.8
Third party / other 2016	4,534	25.3
Too young to vote in 2016	2,415	13.5
Retained (dropped for 2020)	1,665	9.3
Structural NA 2016	203	1.1
Total	17,915	100.0

Note. Entries are counts and column percentages. Rows sum to the 17,915 respondents present in the 2024 analytic sample (n = 84,837) but excluded from the balanced panel (n = 66,922). "Too young" indicates respondents born in 1999 or later (not yet 18 by Election Day 2016, November 8, 2016). "Retained (dropped for 2020)" indicates respondents with valid 2016 major-party vote recall who are nonetheless excluded from the balanced panel due to missing 2020 recall.

Table F2: **Balanced Panel Exclusions by 2020 Vote Recall**

2020 Recall Status	*N*	% of Dropped
Retained (dropped for 2016)	10,815	60.4
Non-voter 2020	5,243	29.3
Third party / other 2020	1,191	6.6
Too young to vote in 2020	568	3.2
Structural NA 2020	98	0.5
Total	17,915	100.0

Note. Entries are counts and column percentages. Rows sum to the 17,915 respondents excluded from the balanced panel (n = 66,922). "Too young" indicates respondents born in 2003 or later (not yet 18 by Election Day 2020, November 3, 2020). "Retained (dropped for 2016)" indicates respondents who voted for a major-party candidate in 2020 but are excluded due to missing 2016 recall. The large share in this category (60.4%) confirms that 2016 exclusions drive the majority of balanced panel attrition.

Table F3 reports the balanced panel retention rate by geographic community type.

Table F3: **Balanced Panel Retention Rate by Geographic Community Type**

Community Type	Total N	Retained N	% Retained
City	22,934	17,015	74.2
Suburb	34,429	28,050	81.5
Town	11,446	9,009	78.7
Rural	16,028	12,848	80.2

Note. Retention rate is the share of respondents in the 2024 analytic sample (n = 84,837) who are also present in the balanced panel (n = 66,922). City residents have the lowest retention rate, consistent with the finding that the dropped respondents skew urban and drive the apparent narrowing in the unbalanced over-time estimates.